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Simulation of Extensive Air Showers with Deep Neural Networks

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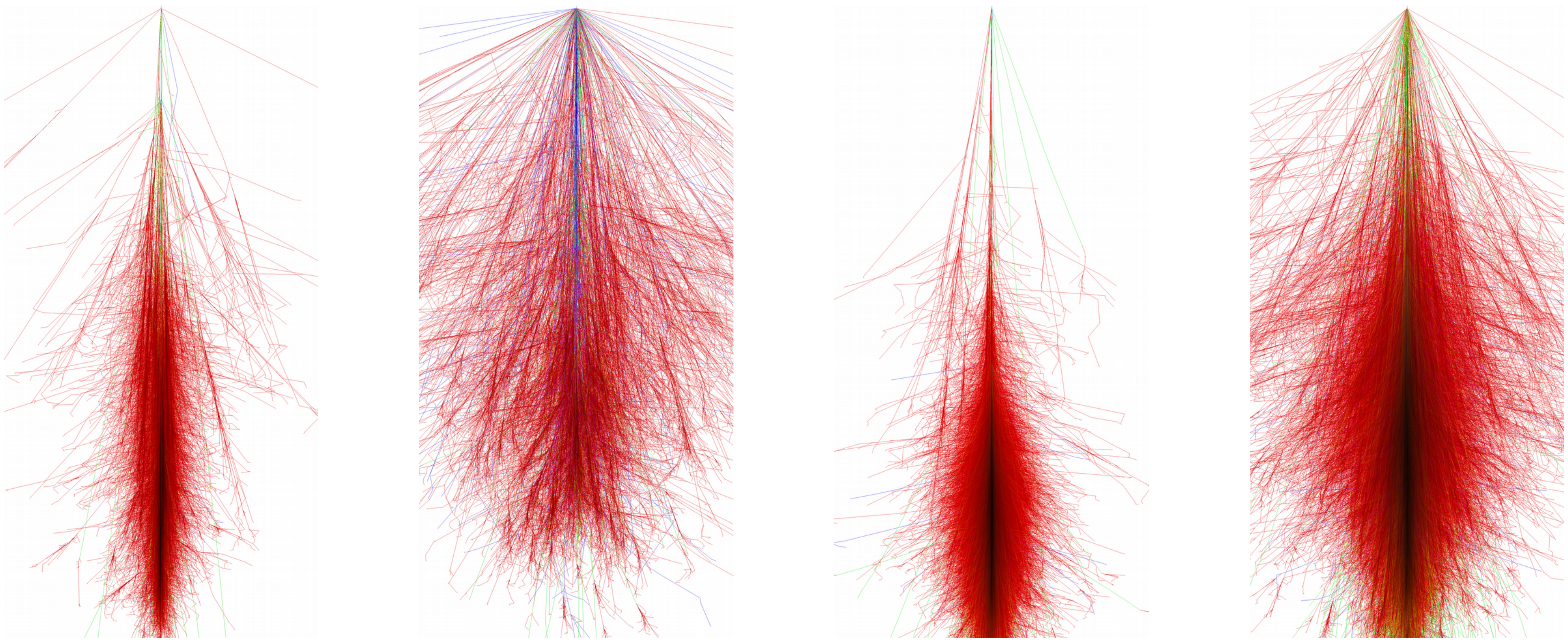
CORSIKA 7 [1]

- Extensive air shower Monte Carlo simulation framework
- Different types of interaction models (EPOS-LHC, QGSJET, SIBYLL, ...)



1 TeV Proton | 1 TeV Iron | 10 TeV Proton | 10 TeV Iron

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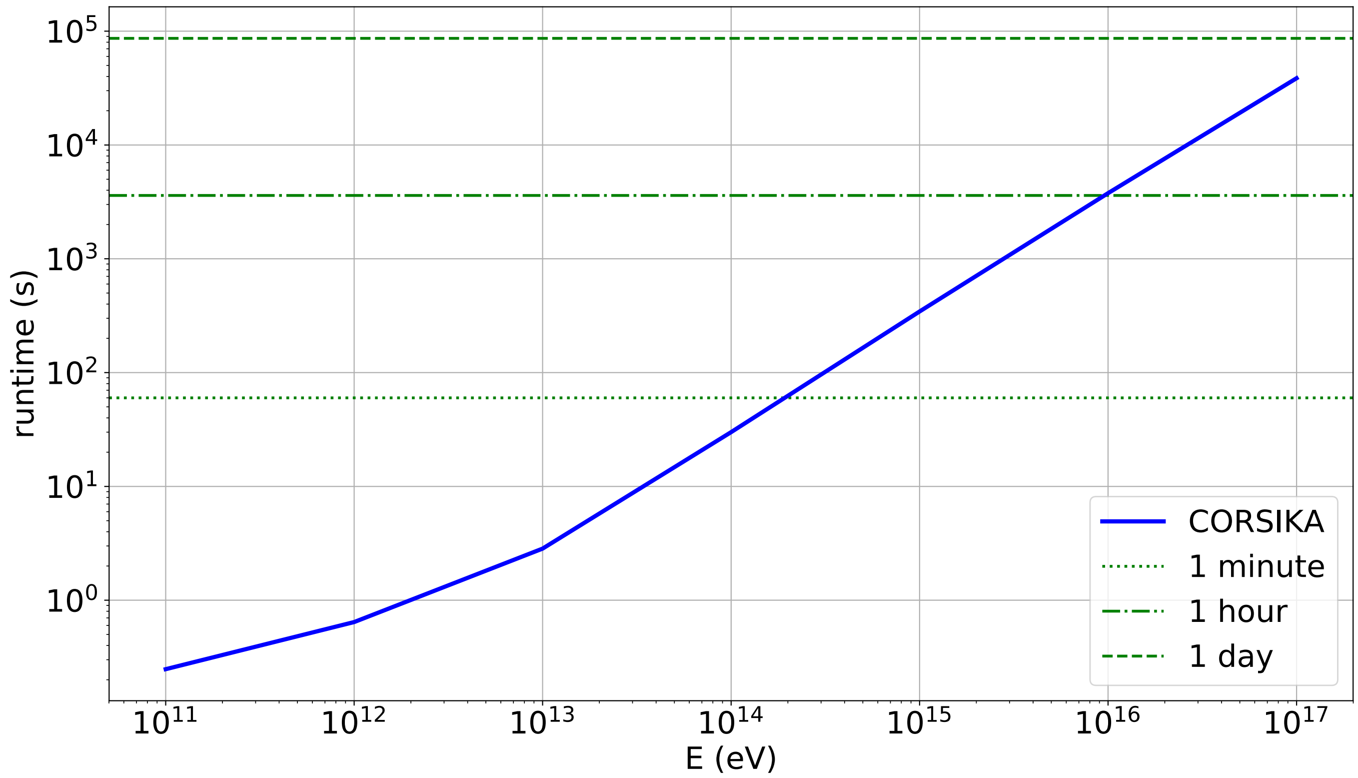
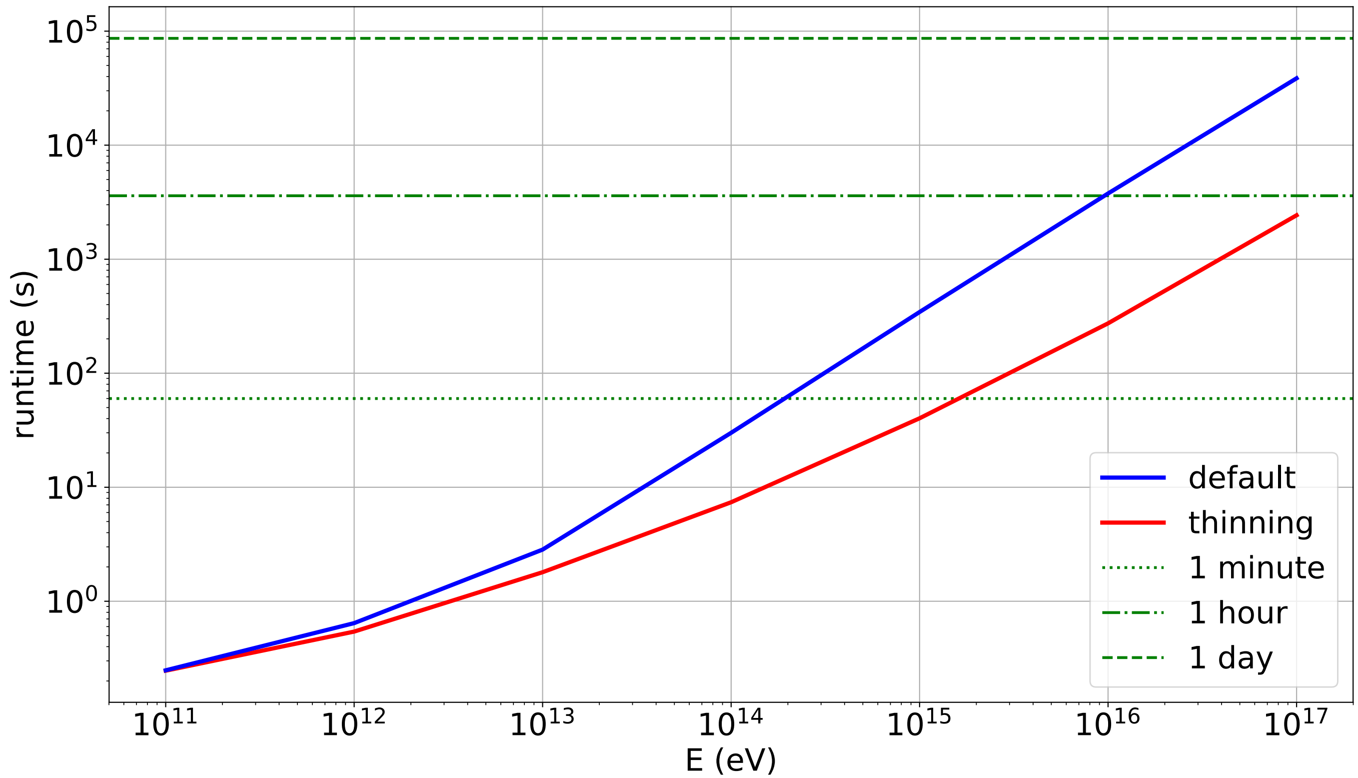
Motivation

- 

- The time complexity of CORSIKA 7 simulations rises approximately linearly with the primary particle energy

Thinning



- Reduces (effective) particle content by particle-aggregation
- Preserves shower properties to leading order
- Reduces shower-to-shower fluctuations

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Why Neural Networks?

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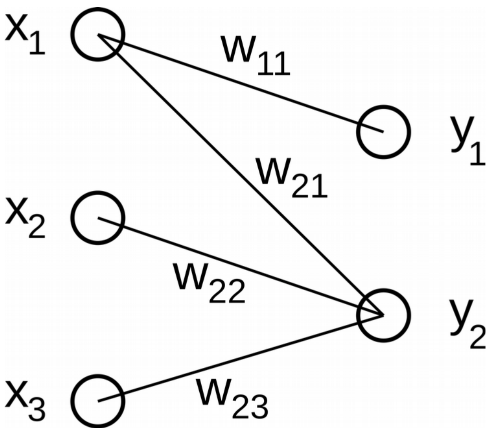
- Can run on specialized **hardware** (GPU / TPU)
- Automatic **parallelization** (TensorFlow)
- Automatic reduction to **essential features**
- Training can **fix meta-parameters**
- **Adjustable accuracy** possible

Neural Networks

- 

$$y_1 = w_{11} \cdot x_1 + w_{12} \cdot x_2 + w_{13} \cdot x_3$$

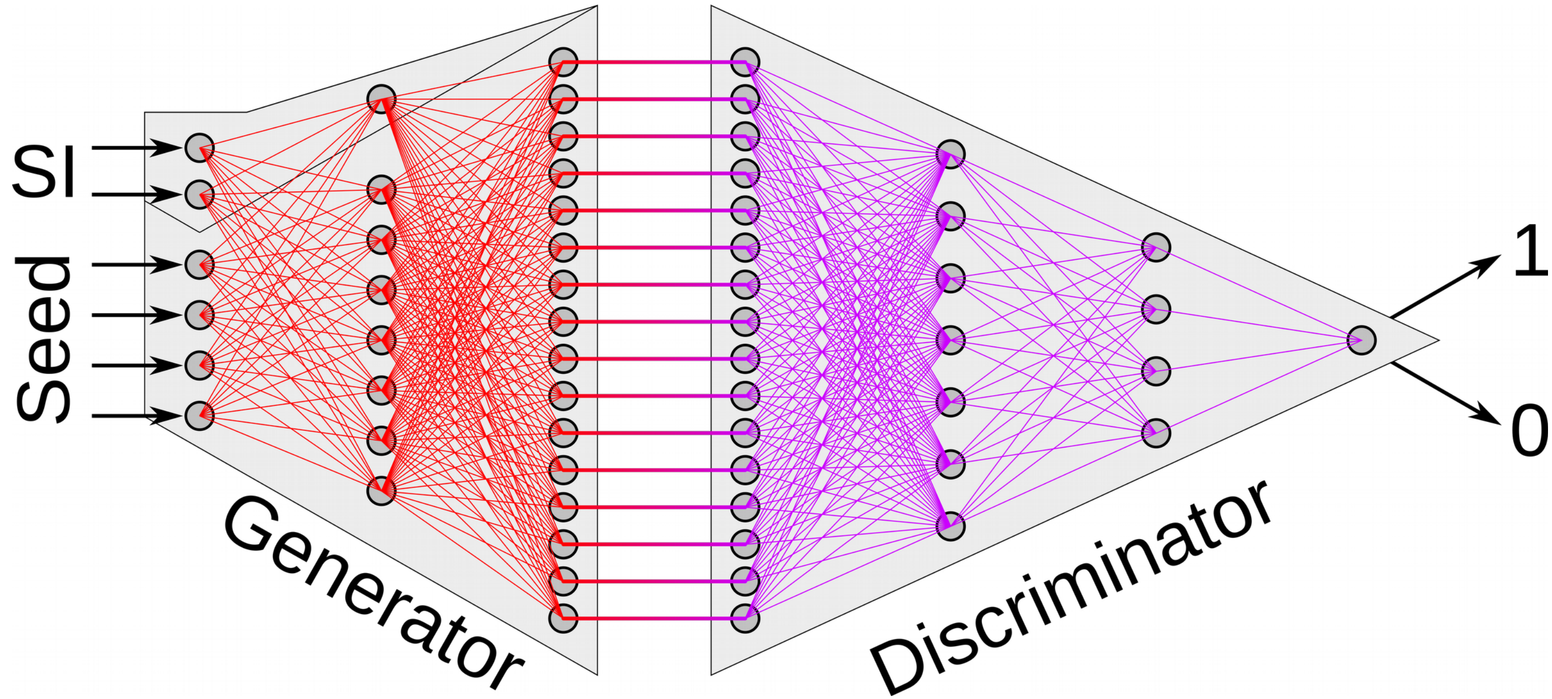
$$y_2 = w_{21} \cdot x_1 + w_{22} \cdot x_2 + w_{23} \cdot x_3$$

$$\vec{y} = w \cdot \vec{x} \ (+\vec{b})$$

$$\vec{f} = a(\vec{y})$$

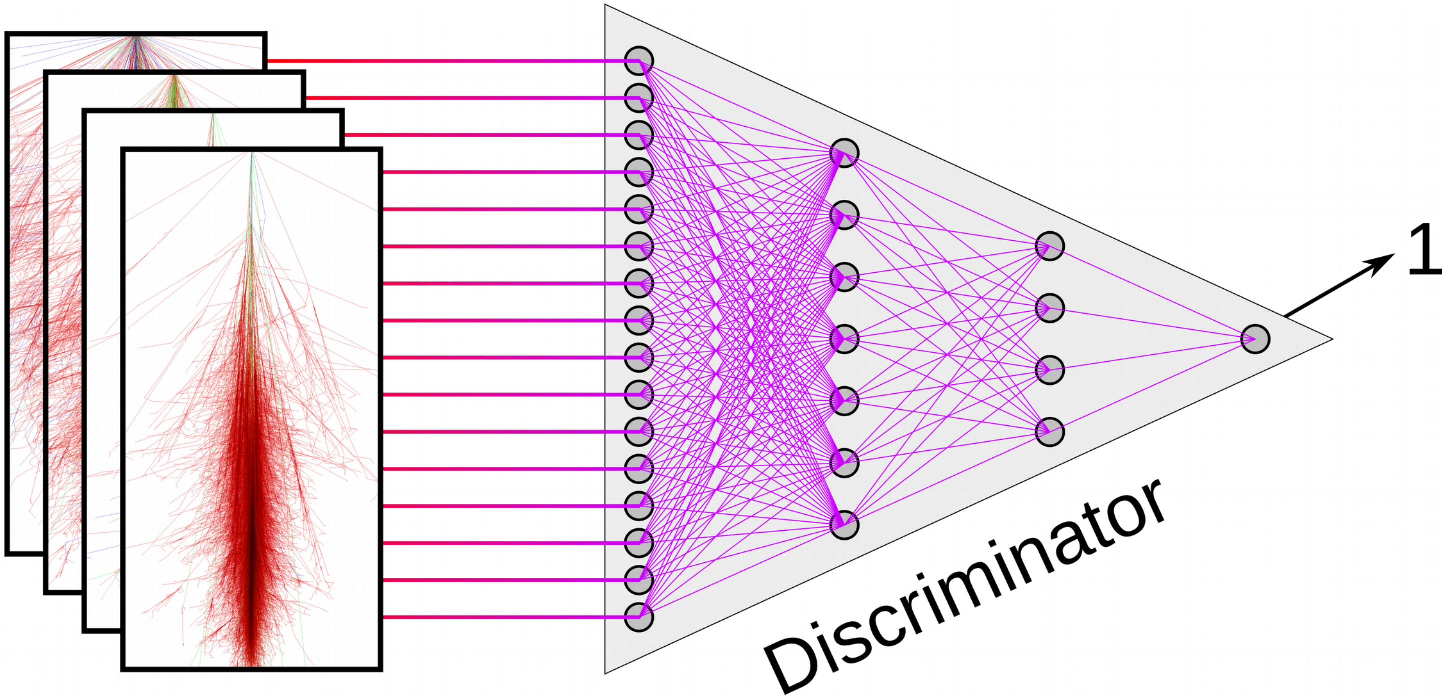
- Combination of linear and non-linear functions
- Training via loss function / metric on data pairs $(\vec{x},\ \vec{t})$
- $L = L(\vec{f}(\vec{x}),\ \vec{t}) \quad \Rightarrow \quad w' = w - \alpha \cdot \nabla_w L$

Generative Adversarial Neural Network (GAN)



- Train discriminator on real (1) and generated (0) data
- Train generator to outsmart the discriminator

Training: Discriminator (Part 1)



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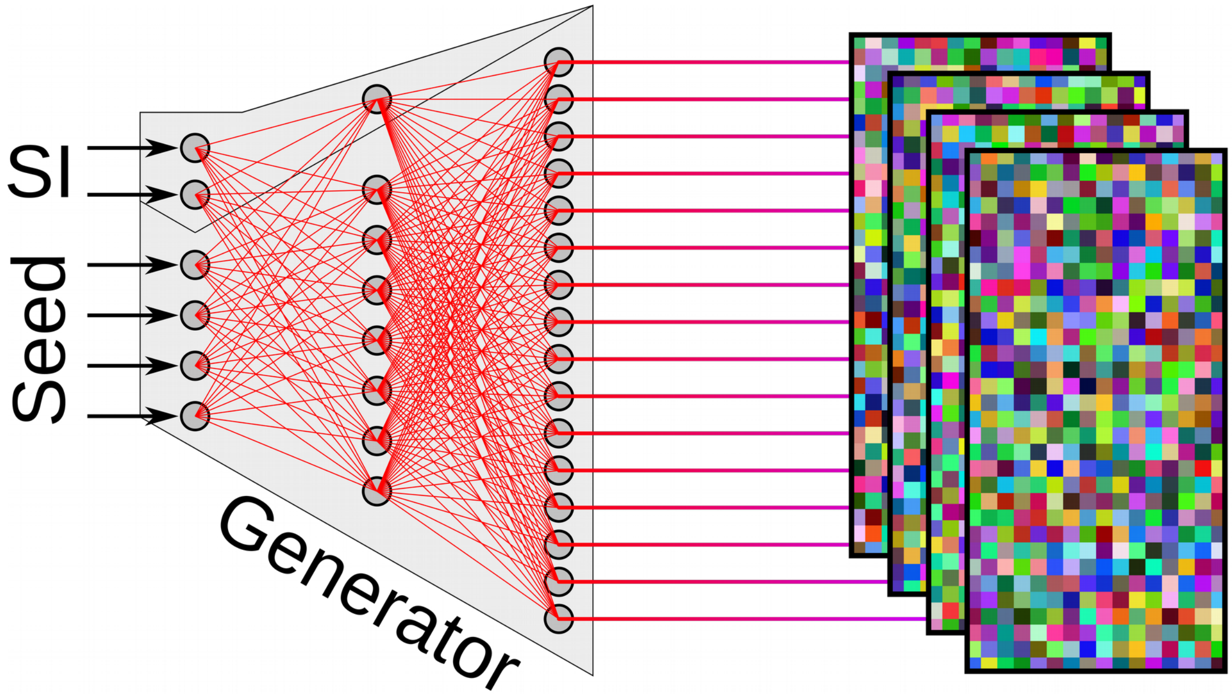
Training: Sampling



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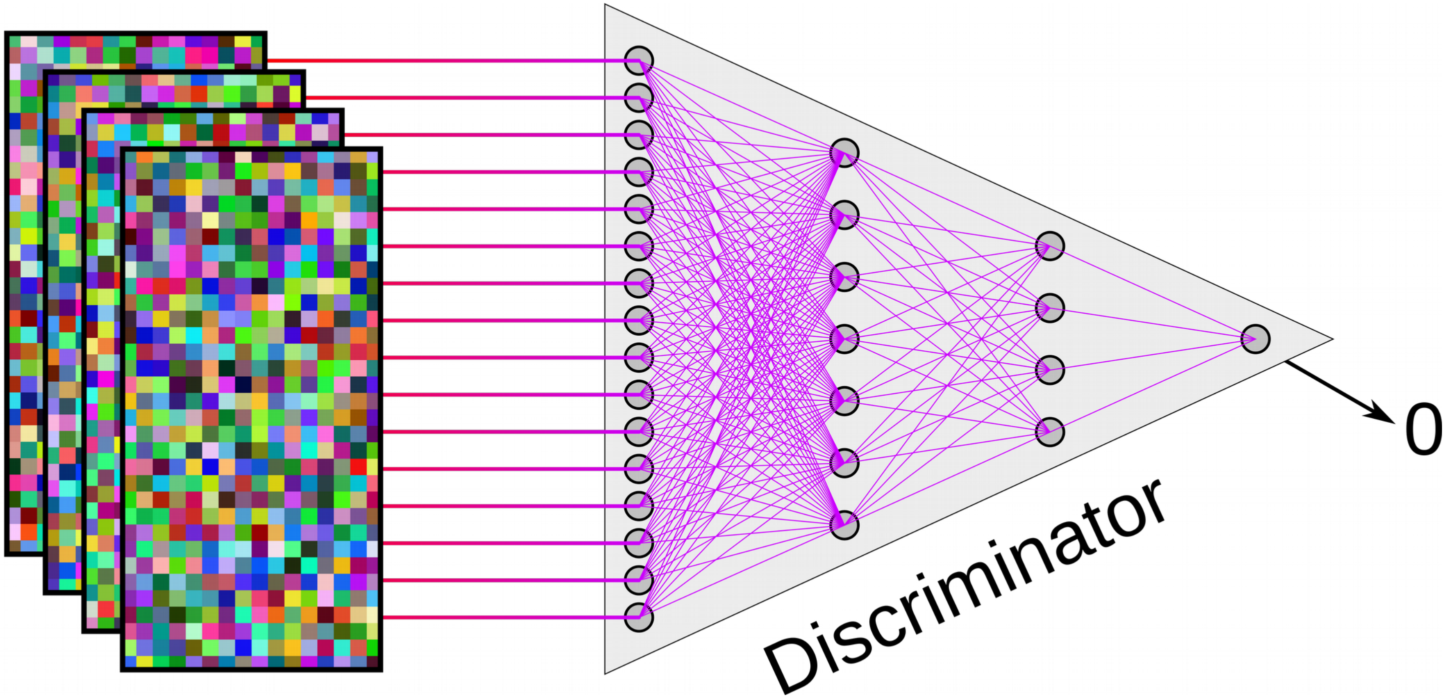
Training: Discriminator (Part 2)



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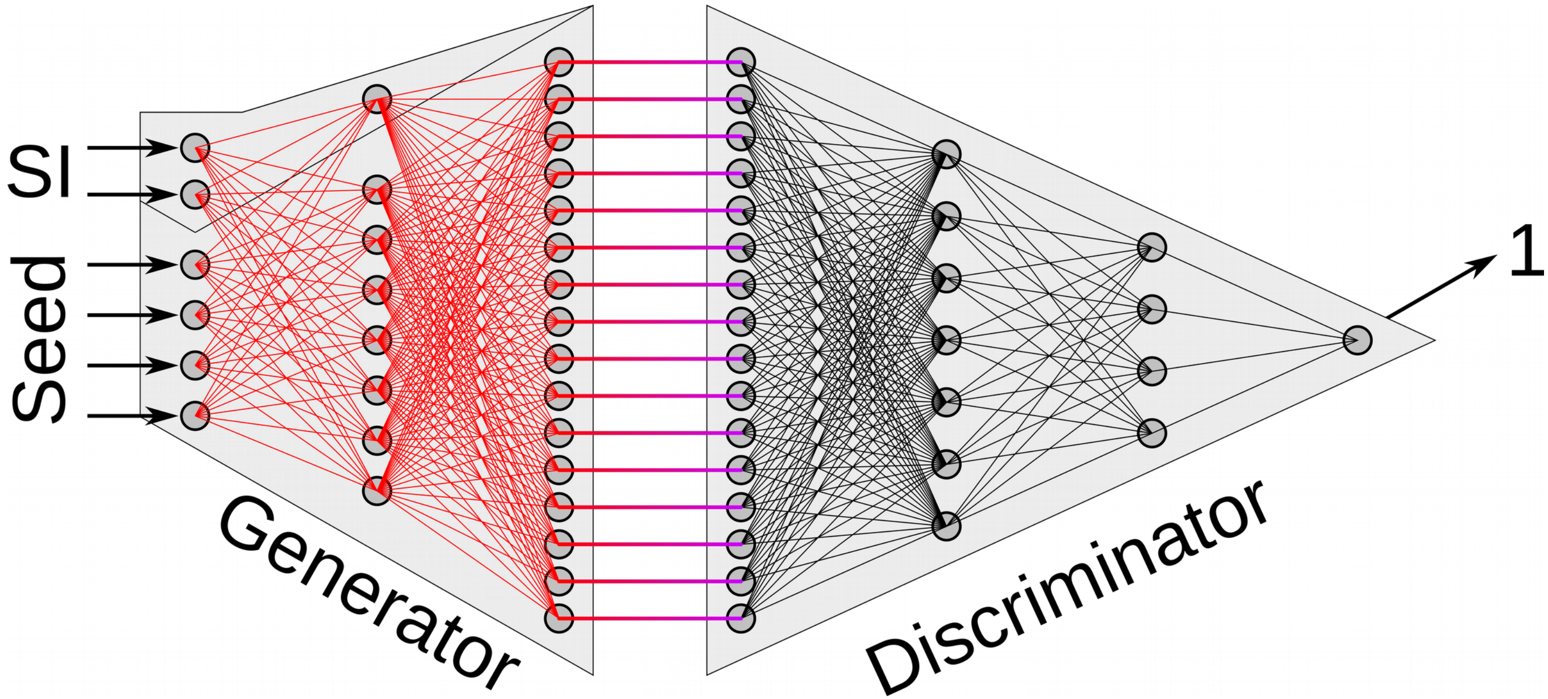
Training: Generator



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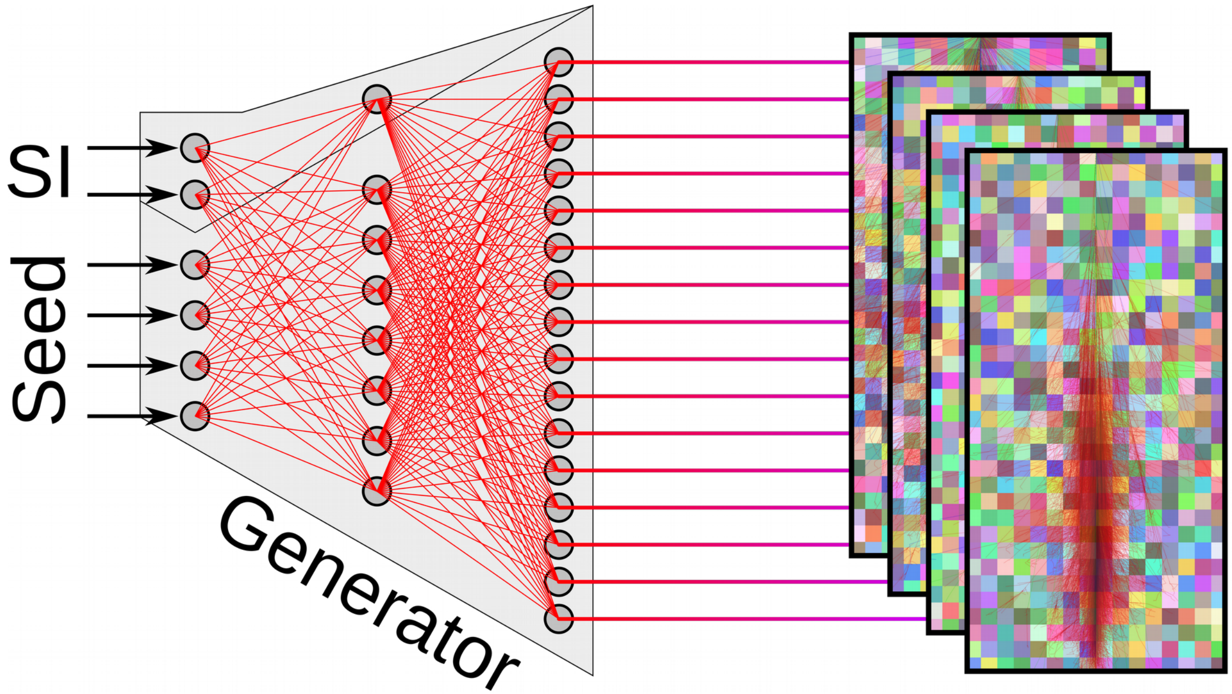
Training: Result



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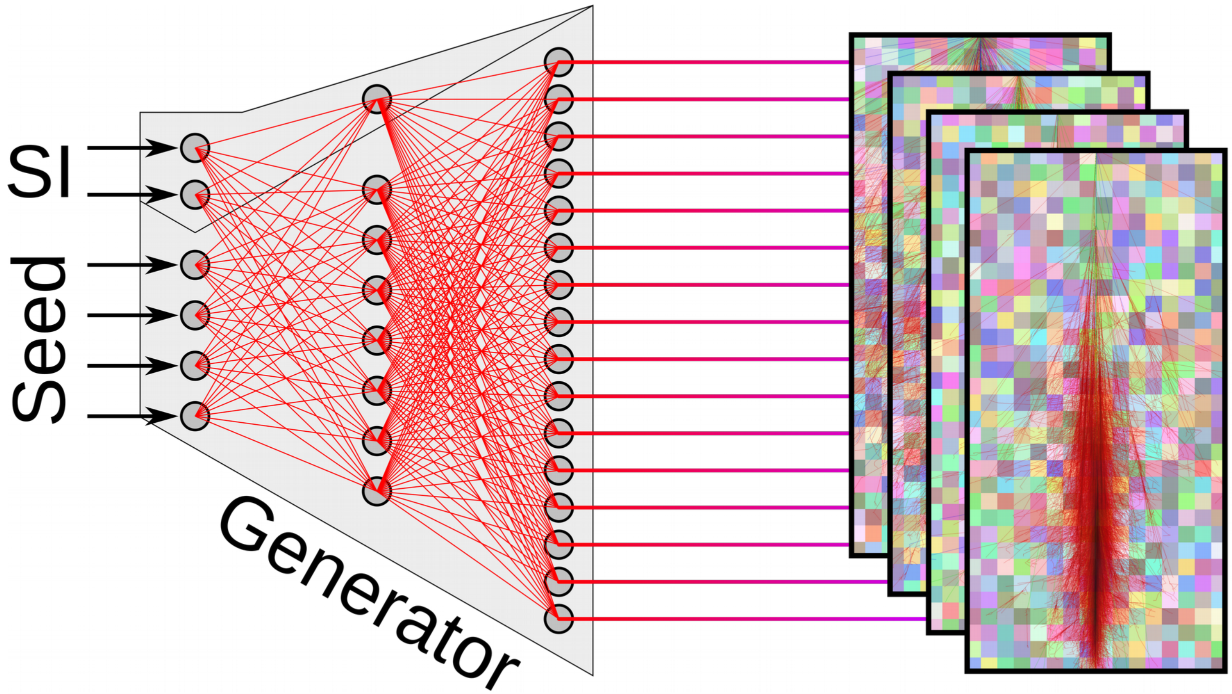
Training: Result



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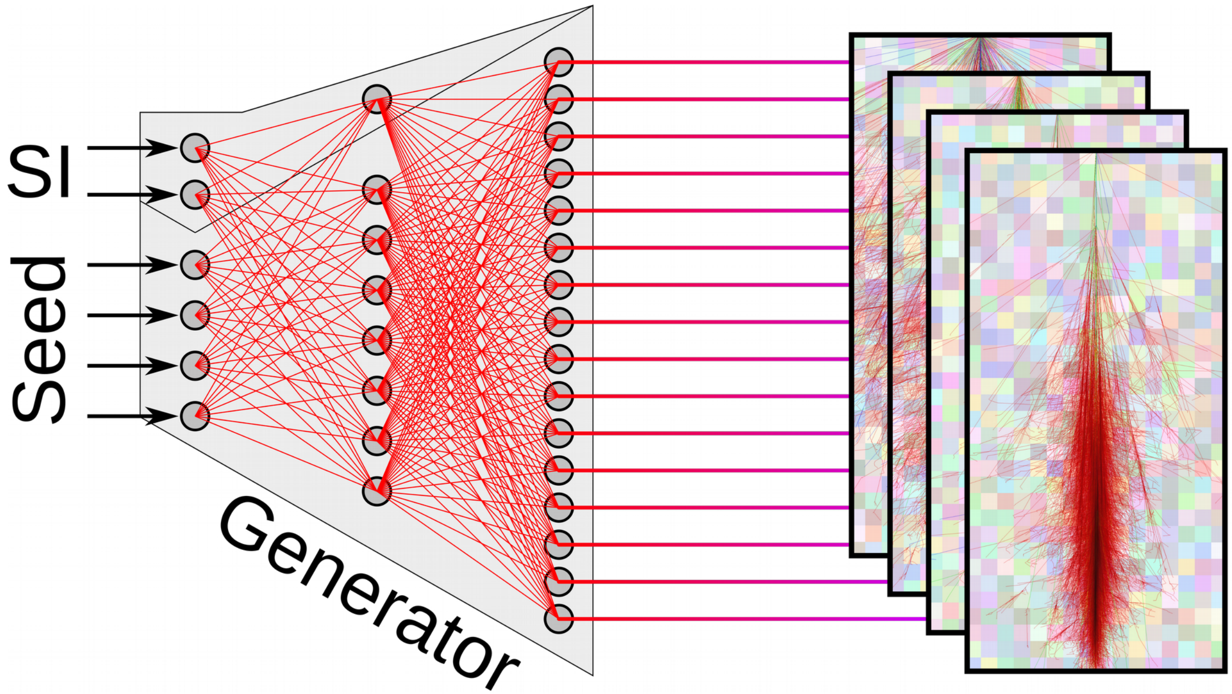

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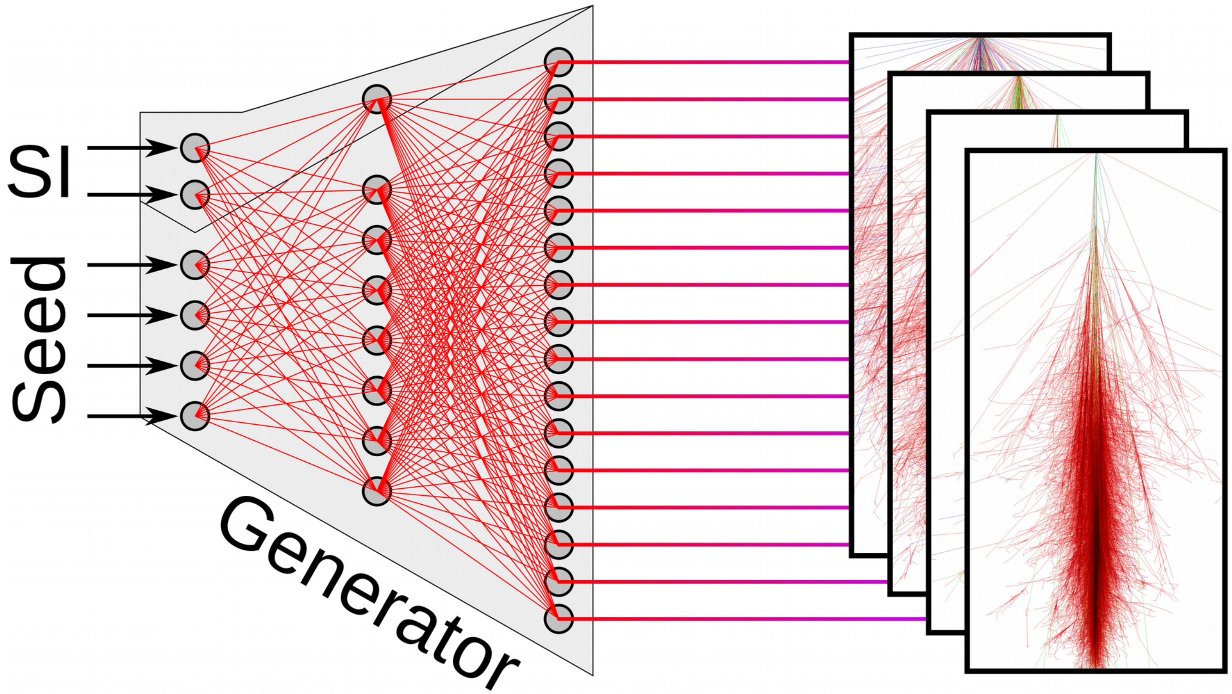
Training: Result



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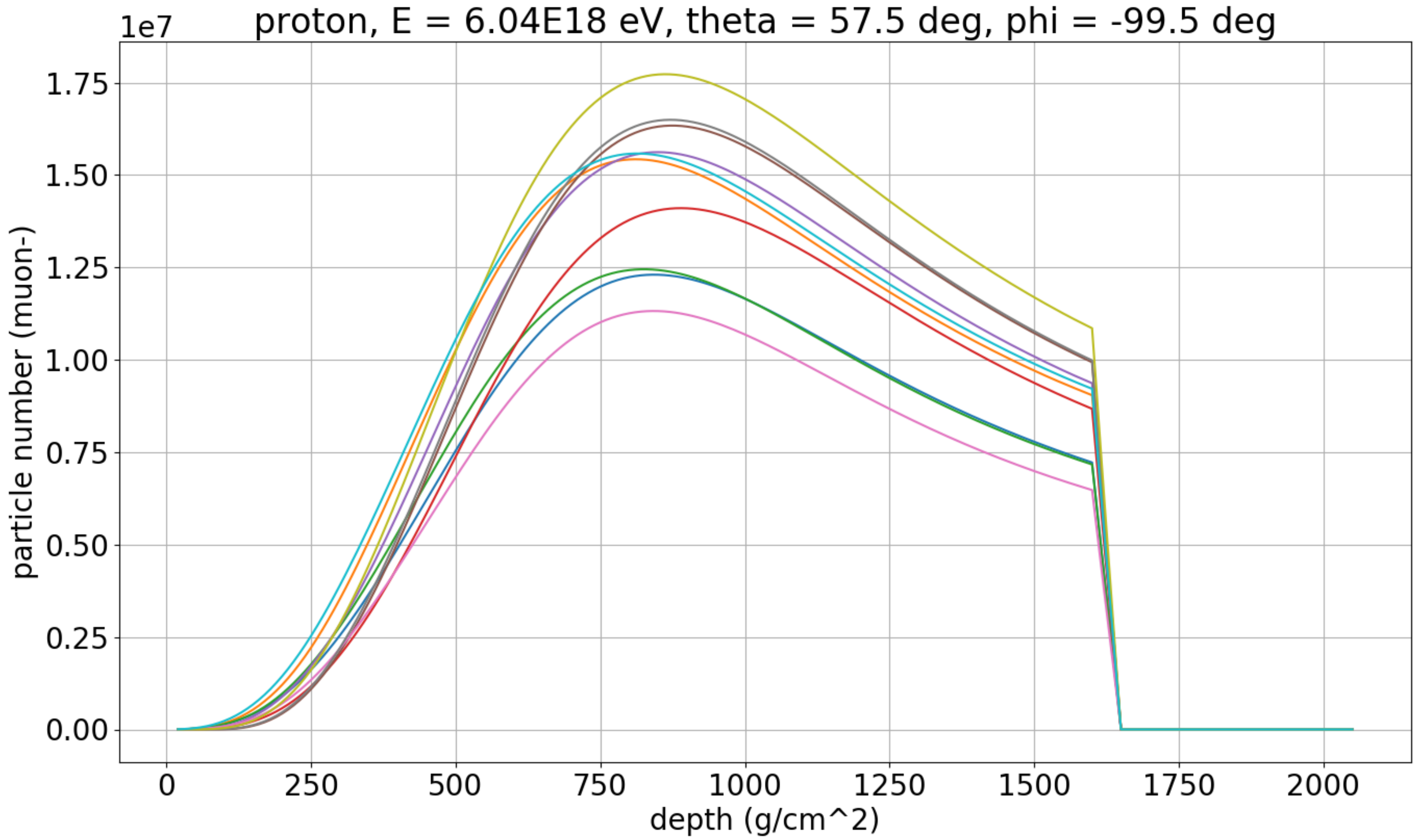
First Test (CONEX)

- CONEX: Hybrid Extenisve Air Shower Simulation
  - first: Monte Carlo until energy threshold (3D)
  - then: cascade equation solver (1D)
  - provides longitudinal profile only
  - runtime: seconds – minutes

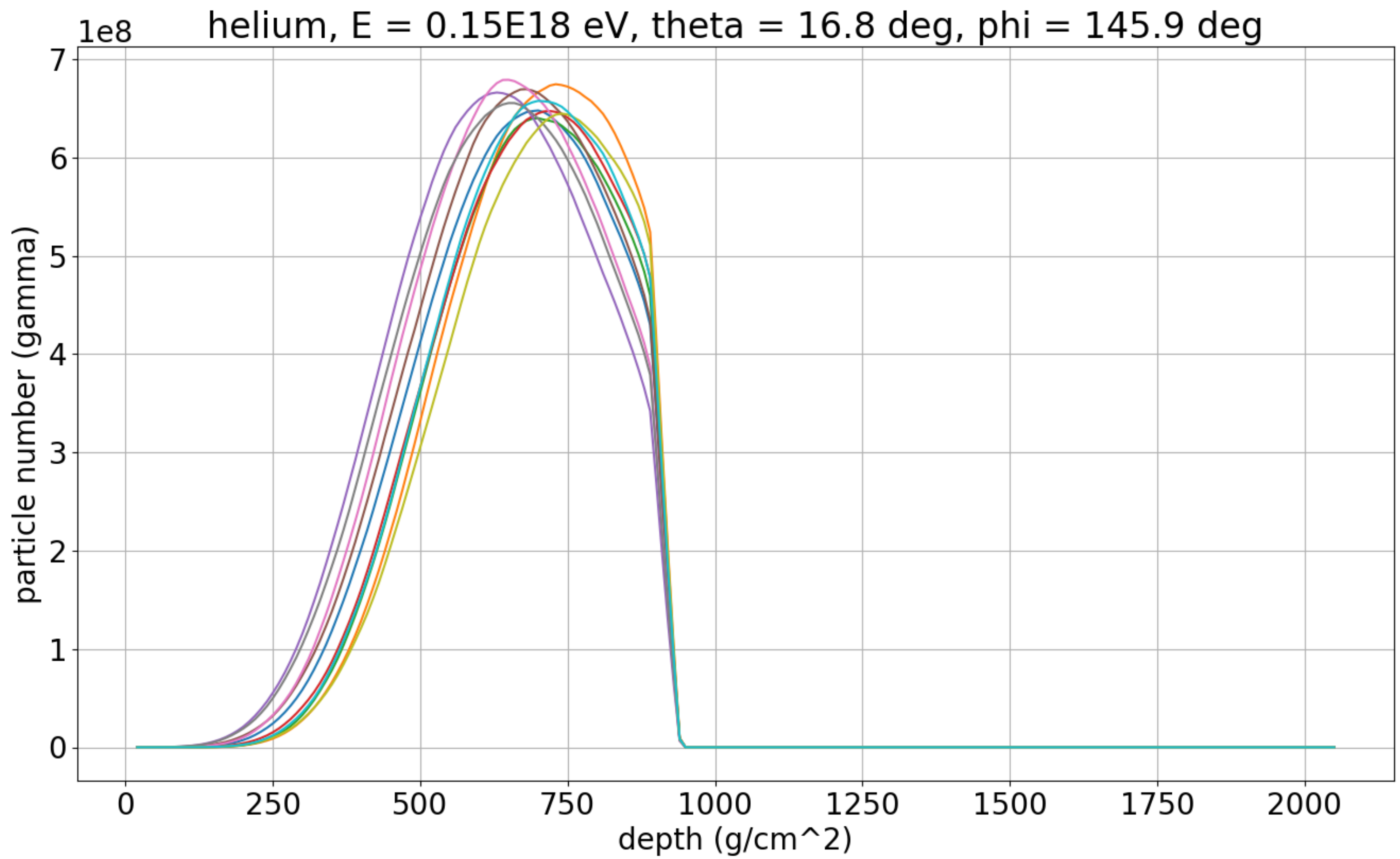
- Configuration:
  - E = 1E17 ... 1E19 eV
  - Zenith = 0 ... 65 deg
  - Azimuth = -180 ... 180 deg

- Generated ~187k datapoints

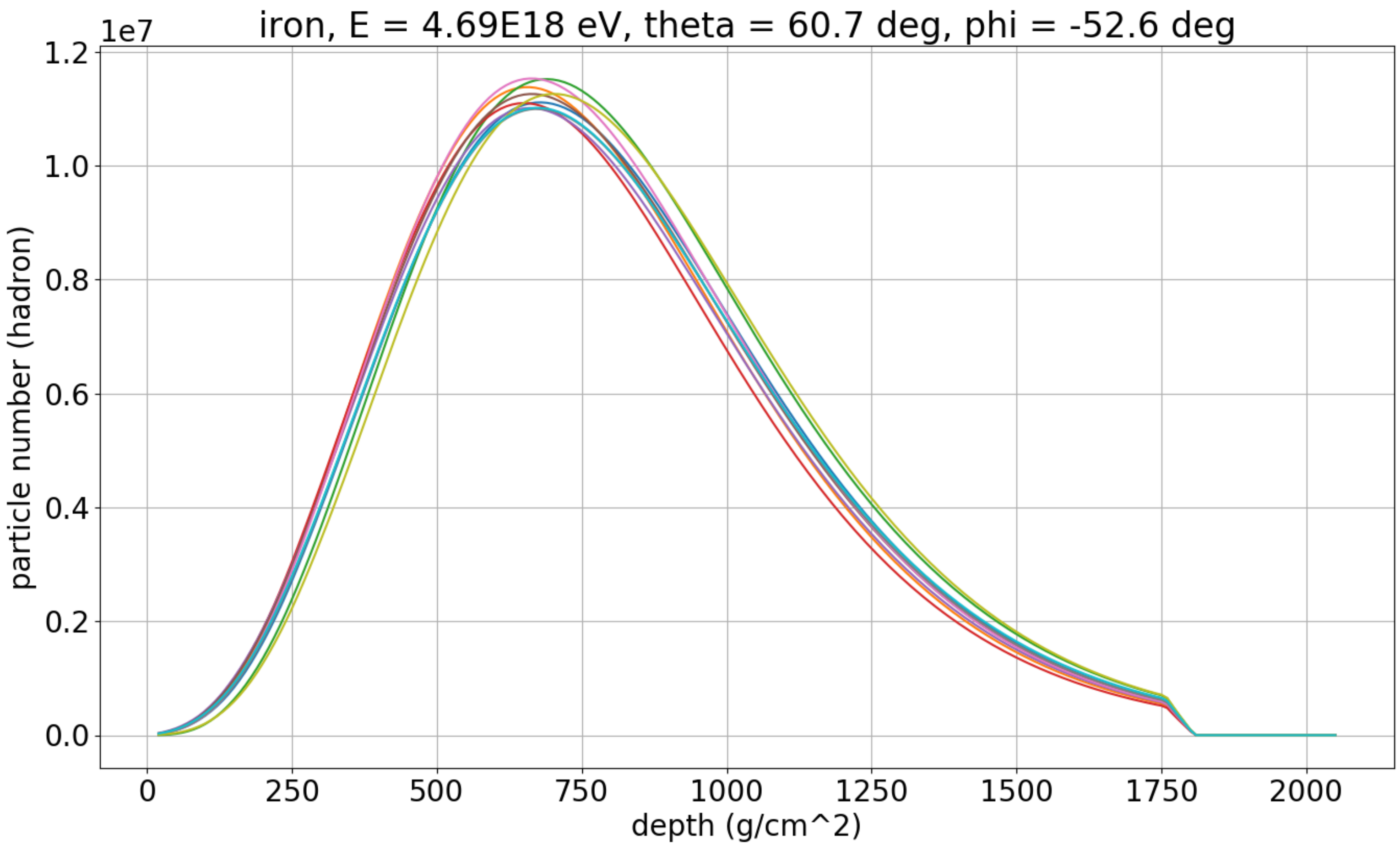
Shower-to-Shower Fluctuations



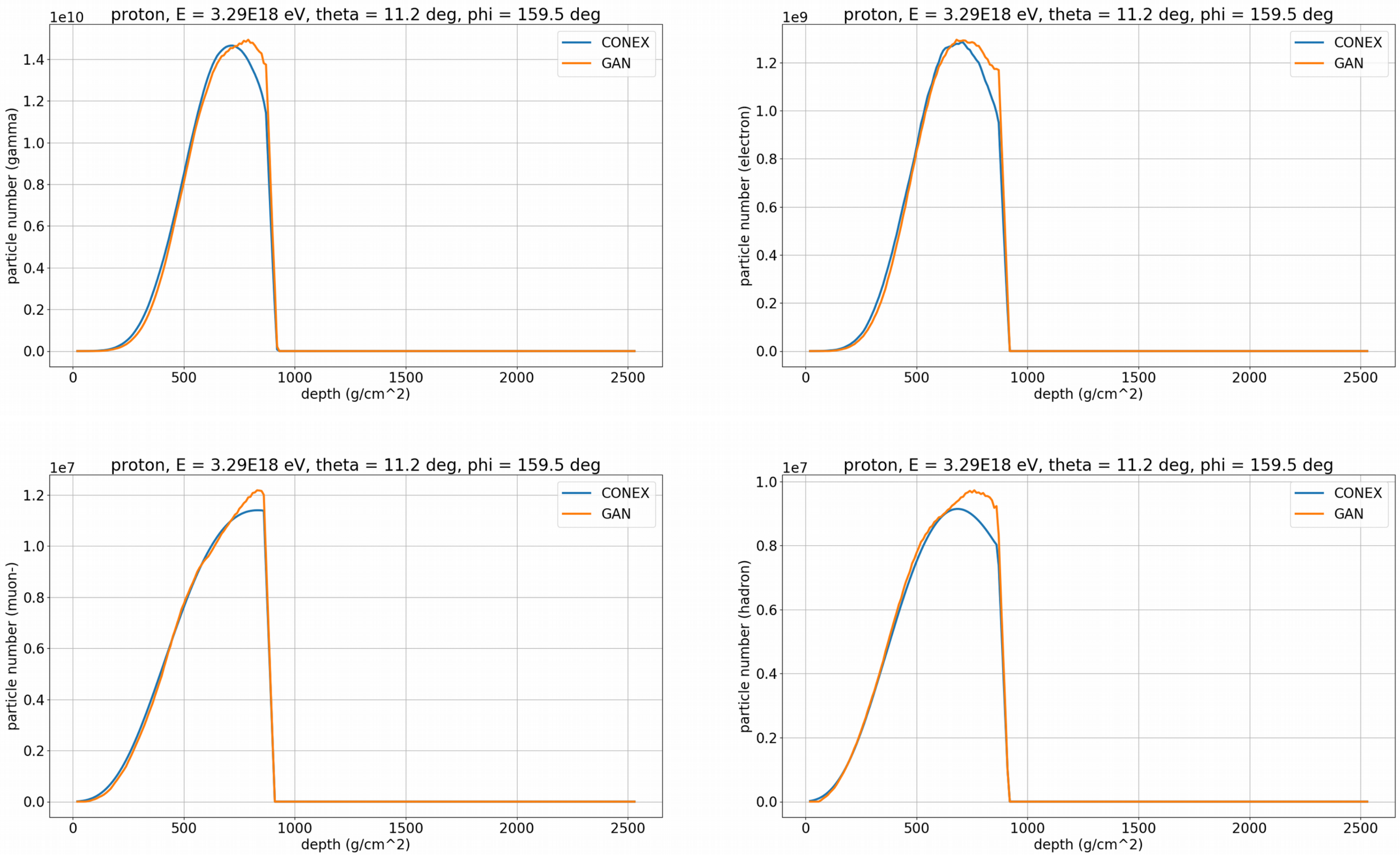
Shower-to-Shower Fluctuations



Shower-to-Shower Fluctuations

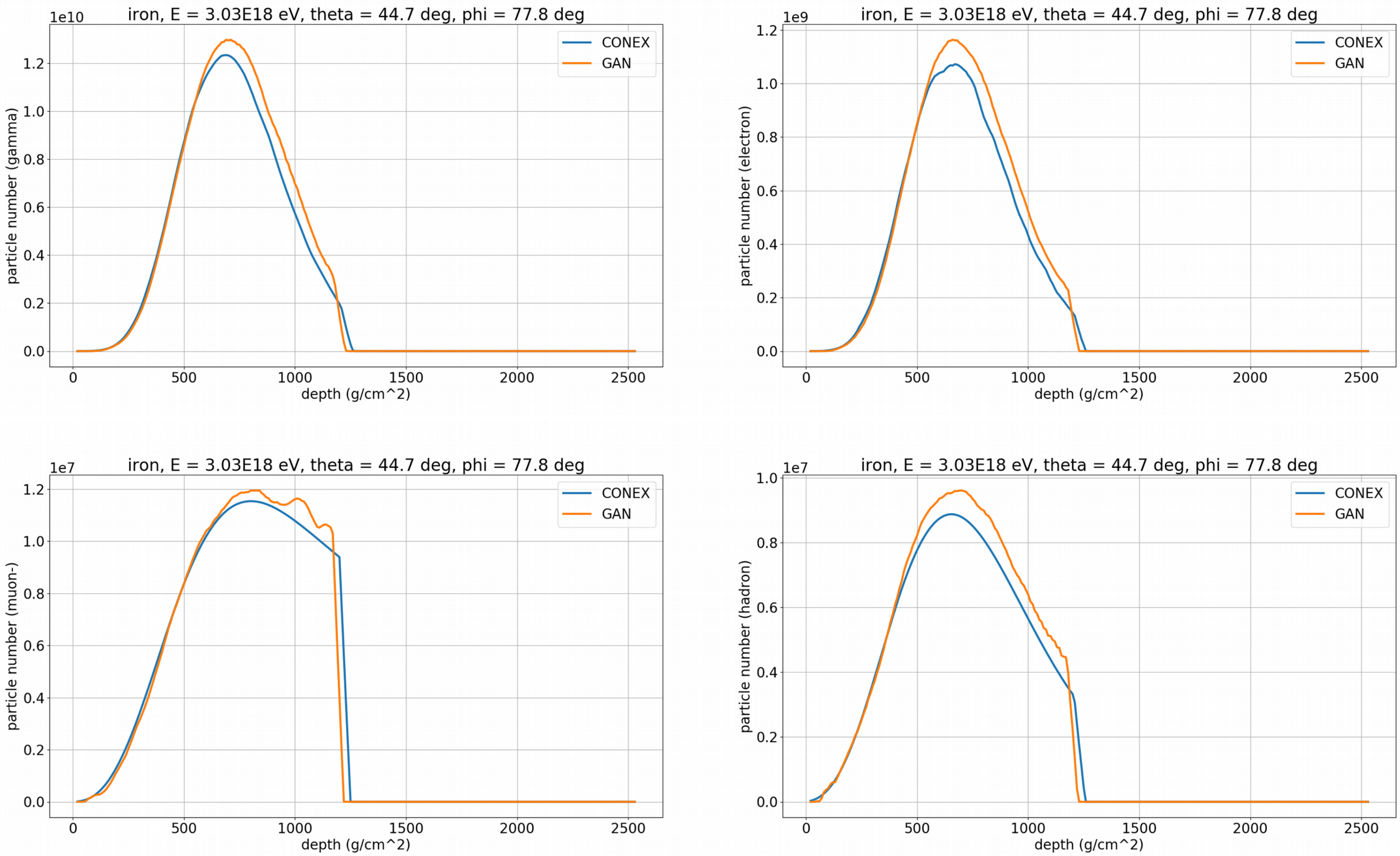


CONEX vs. GAN



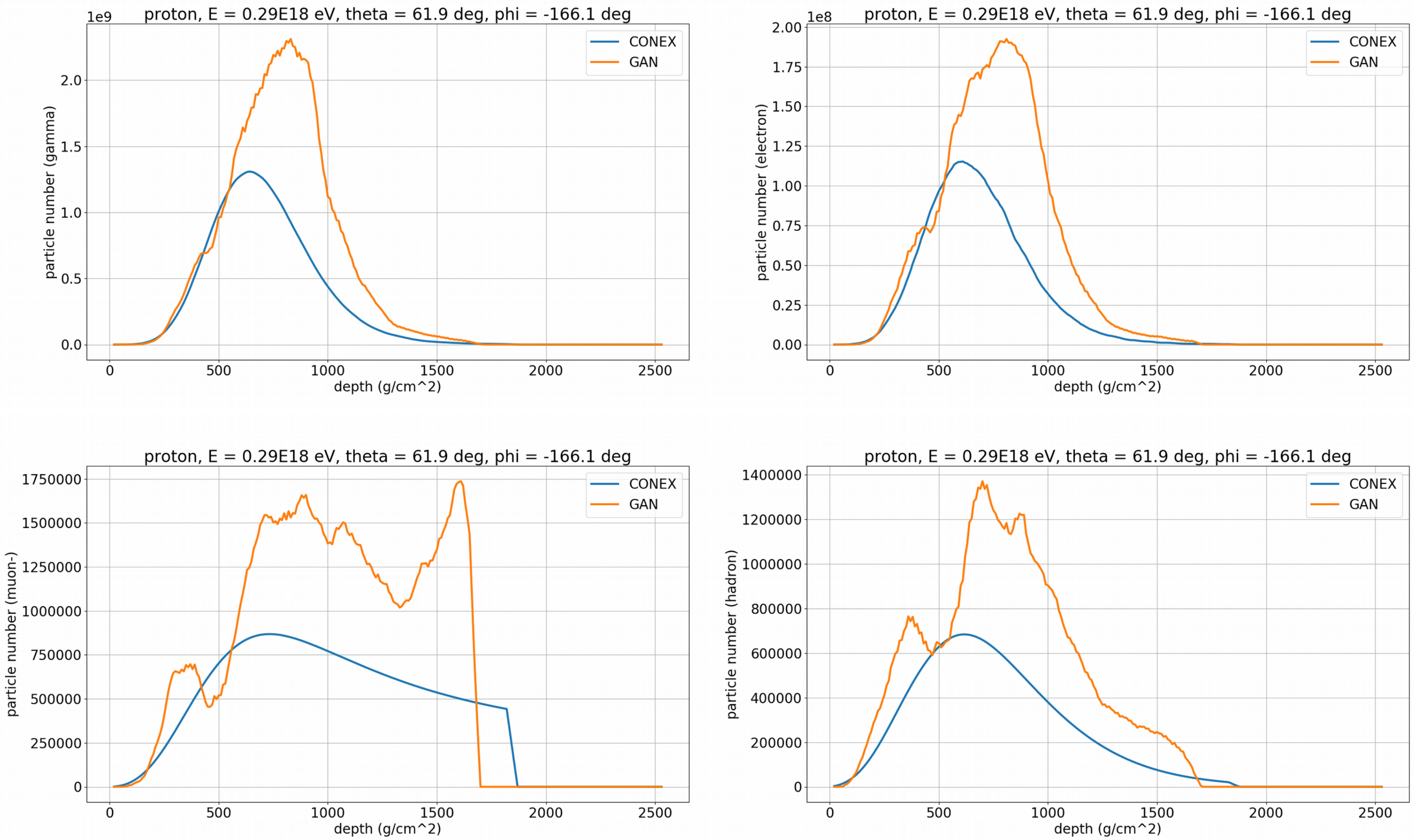
proton, E = 3.29E18 eV, theta = 11.2 deg, phi = 159.5 deg
1e10
particle number (gamma)
depth (g/cm^2)
CONEX
GAN
proton, E = 3.29E18 eV, theta = 11.2 deg, phi = 159.5 deg
1e9
particle number (electron)
depth (g/cm^2)
CONEX
GAN
proton, E = 3.29E18 eV, theta = 11.2 deg, phi = 159.5 deg
1e7
particle number (muon-)
depth (g/cm^2)
CONEX
GAN
proton, E = 3.29E18 eV, theta = 11.2 deg, phi = 159.5 deg
1e7
particle number (hadron)
depth (g/cm^2)
CONEX
GAN

CONEX vs. GAN

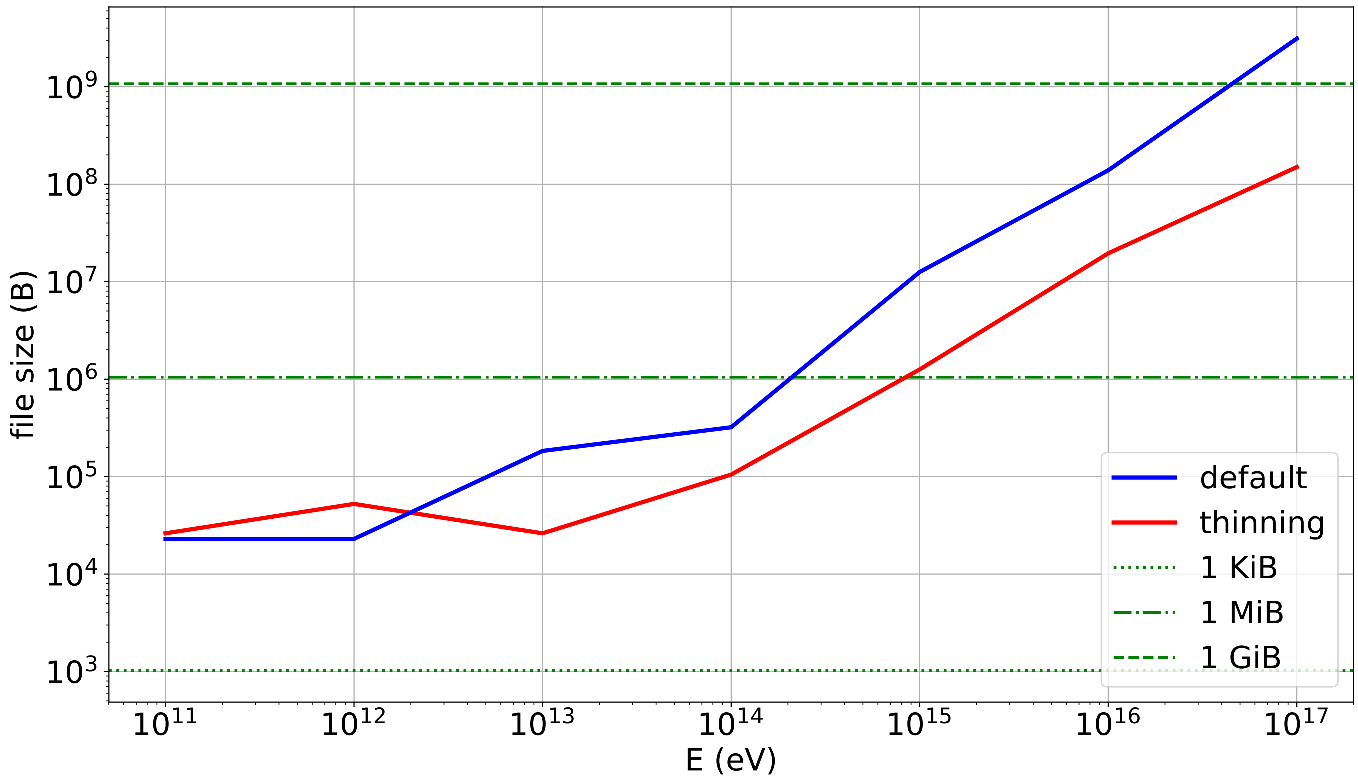


iron, E = 3.03E18 eV, theta = 44.7 deg, phi = 77.8 deg
1e10
particle number (gamma)
depth (g/cm^2)
CONEX
GAN
iron, E = 3.03E18 eV, theta = 44.7 deg, phi = 77.8 deg
1e9
particle number (electron)
depth (g/cm^2)
CONEX
GAN
iron, E = 3.03E18 eV, theta = 44.7 deg, phi = 77.8 deg
1e7
particle number (muon-)
depth (g/cm^2)
CONEX
GAN
iron, E = 3.03E18 eV, theta = 44.7 deg, phi = 77.8 deg
1e7
particle number (hadron)
depth (g/cm^2)
CONEX
GAN

CONEX vs. GAN


proton, E = 0.29E18 eV, theta = 61.9 deg, phi = -166.1 deg
1e9
particle number (gamma)
depth (g/cm^2)
CONEX
GAN
1e8
particle number (electron)
particle number (muon-)
particle number (hadron)

Shower Library



- Shower library required for analyses and model training
- Trained model = effective compression of shower library

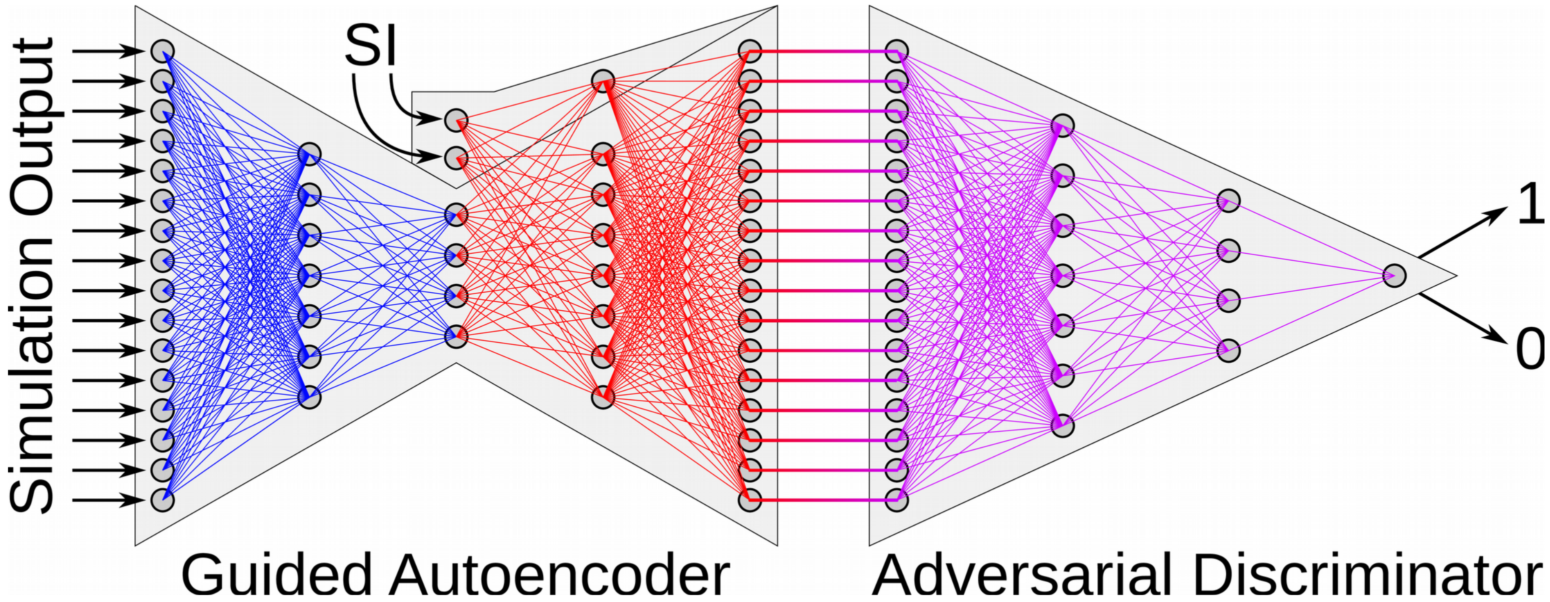
Summary

- Deep Neural Networks can serve as an effective simulation heuristic
- Can improve runtime and (effective) data compression
- Can employ specialized hardware
- Trained models can be conditioned on meta-parameters
- Adjustable accuracy is possible
- ErUM: Innovative Digitale Technologien zur Erforschung von Universum und Materie

Backup

Fast Implicit Simulation Heuristic (FISH)

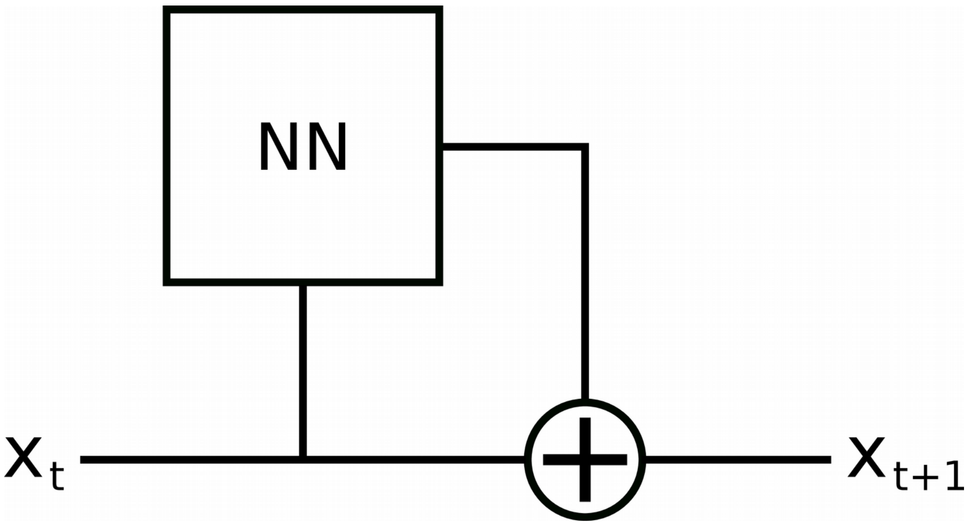
- Autoencoder with Adversarial Metric



- Simulation Input (SI) can be extended with meta-parameters
- Discriminator can be refined with real measurements

Adjustable Accuracy [2]

- ResNet



- Translate to ordinary differential equation (ODE)

$$x_{t+1} = x_t + f(x_t, \theta_t) \quad \Rightarrow \quad \frac{dx(t)}{dt} = f(x(t), t, \theta)$$

- Solve with standard ODE solver

- Adapt solver accuracy on the fly (training: high, inference: low)

Working Example [3]

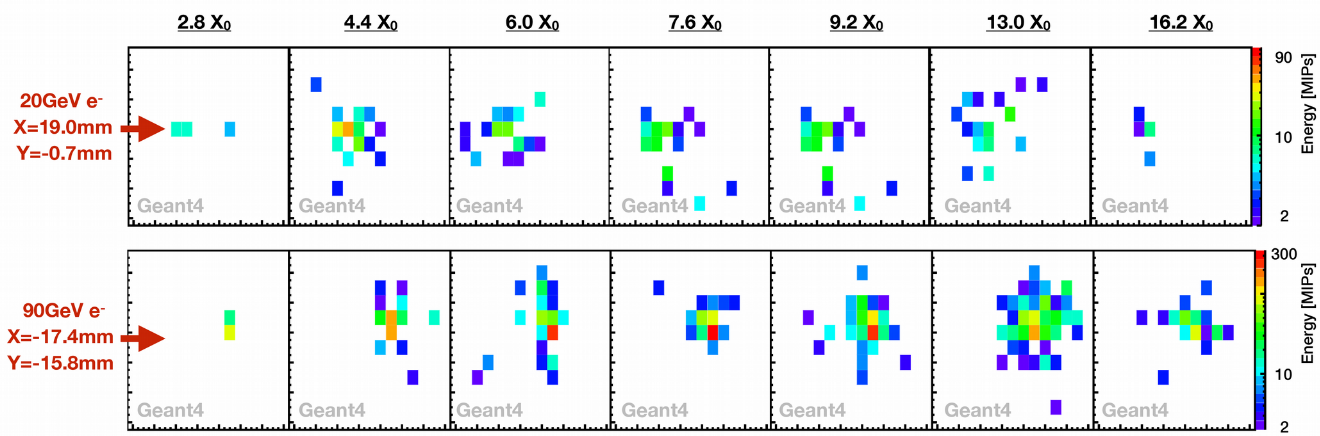
- „Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network“ - Martin Erdmann, Jonas Glombitza, Thorben Quast – arXiv: 1807.01954

<u>Some Highlights:</u>

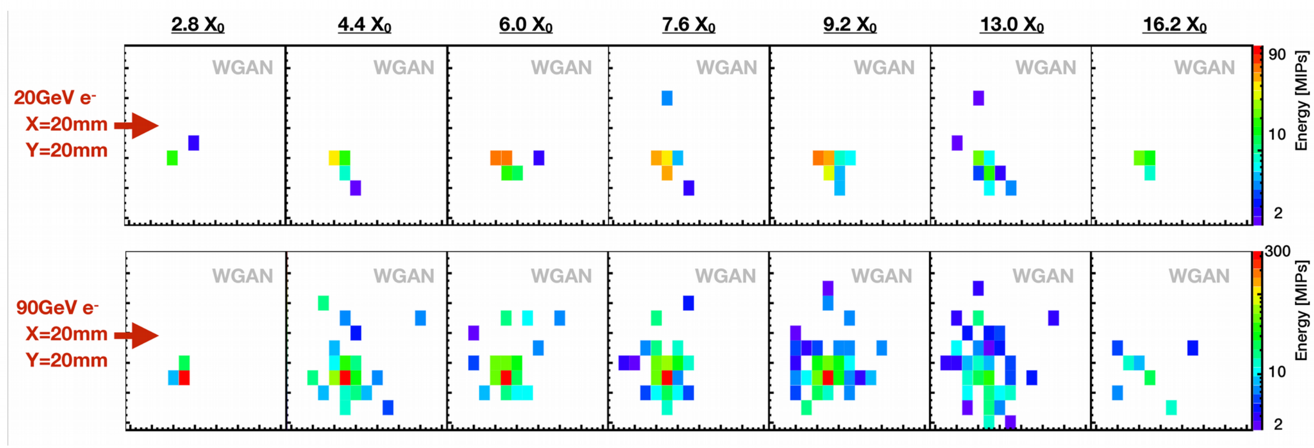
- **Wasserstein GAN** for HEP Geant4 simulations
- **Interpolation** between training energies
- Up to **x6660 faster** than Geant4
- Runtime is **independent of particle energy**

Geant4 vs. Wasserstein GAN [3]

- Geant4:



- Wasserstein GAN:



References

- Title picture:
  Karlsruhe Castle - Meph666 [CC BY-SA 3.0]
  https://commons.wikimedia.org/wiki/File:Karlsruhe-Schloss-meph666-2005-Apr-22.jpg

- Backup picture:
  Photo by Anthony from Pexels

- [1] CORSIKA 7: https://www.ikp.kit.edu/corsika/

- [2] „Neural Ordinary Differential Equations“ - Ricky T. Q. Chen, Yulia Rubanova, Jesse Bettencourt, David Duvenaud – arXiv: 1806.07366

References

- [3] „Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network“ - Martin Erdmann, Jonas Glombitza, Thorben Quast – arXiv: 1807.01954